System Dynamics Modeling of the Time Course of the Recognition-Primed Decision Model

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ABSTRACT: Two types of decision-making processes have been identified in the literature: an analytical process and an intuitive process. One conceptual model of the latter is the recognition-primed decision (RPD) model (e.g., Klein, 2008). According to this model, decision making in naturalistic contexts entails a situational pattern-recognition process that, if subsequent expectancies are confirmed, leads the decision maker to render a decision to engage in a given course of action. In this paper, we describe a system dynamics model of Klein's RPD framework that focuses upon the dynamics of the decision-making process. The structure of our RPD model is based on a model of a set of laboratory phenomena called *conjunction benefits and costs* (e.g., L. R. Fournier, Patterson, Dyre, Wiediger, & Winters, 2007), which was extended to encompass the RPD framework. The results of our simulations suggest that decision priming (a bias toward rendering a given decision based on prior information) is a phenomenon that should occur in many naturalistic settings.

Introduction

MANY AUTHORS (E.G., EVANS, 1984, 2003, 2008; HAMMOND, 2007; HOGARTH, 2001; Kahneman & Frederick, 2002; Sloman, 1996; Stanovich & West, 2000) have recently proposed that human decision making is composed of a blend of two complementary systems, an analytical system and an intuitive or heuristic system, which compete for control of thinking and reasoning. Analytical decision making refers to making conscious decisions that entail the contrasting of options and the assessment of their likelihood and possible consequences. Evans (2003) has argued that the analytical system is evolutionarily recent, permits abstract reasoning, is correlated with measures of general intelligence, and is constrained by working memory capacity. Many authors have argued that this system is slow, deliberative, effortful, abstract, rule-based, and symbolic.

		Form Approved
# Report Documentation Page		OMB No. 0704-0188

1. REPORT DATE	2. REPORT TYPE	3. DATES COVERED
OCT 2009	**Journal Article**	**01-01-2008 to 30-09-2009**

4. TITLE AND SUBTITLE	5a. CONTRACT NUMBER
System Dynamics Modeling of the Time Course of the Recognition-Primed Decision Model	**FA8650-05-D-6502 TO 37**
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER **62205F**

6. AUTHOR(S)	5d. PROJECT NUMBER
Robert Patterson; Lisa Fournier; Byron Pierce; Marc Winterbottom; Lisa Tripp	**1123**
	5e. TASK NUMBER **AE**
	5f. WORK UNIT NUMBER **07**

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)	8. PERFORMING ORGANIZATION REPORT NUMBER
Air Force Research Laboratory/RHA,Warfighter Readiness Research Division,6030 South Kent Street,Mesa,AZ,85212-6061	**AFRL; AFRL/RHA**

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR'S ACRONYM(S)
Air Force Research Laboratory/RHA, Warfighter Readiness Research Division, 6030 South Kent Street, Mesa, AZ, 85212-6061	**AFRL; AFRL/RHA**
	11. SPONSOR/MONITOR'S REPORT NUMBER(S) **AFRL-RH-AZ-JA-2009-0006**

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

13. SUPPLEMENTARY NOTES
Published in the Journal of Cognitive Engineering and Decision Making, 3(3), 253-279

14. ABSTRACT

Two types of decision-making processes have been identified in the literature: an analytical process and an intuitive process. One conceptual model of the latter is the recognition-primed decision (RPD) model (e.g., Klein, 2008). According to this model, decision making in naturalistic contexts entails a situational pattern-recognition process that, if subsequent expectancies are confirmed, leads the decision maker to render a decision to engage in a given course of action. In this paper, we describe a system dynamics model of Klein's RPD framework that focuses upon the dynamics of the decision-making process. The structure of our RPD model is based on a model of a set of laboratory phenomena called conjunction benefits and costs (e.g., L. R. Fournier, Patterson, Dyre, Wiediger, & Winters, 2007), which was extended to encompass the RPD framework. The results of our simulations suggest that decision priming (a bias toward rendering a given decision based on prior information) is a phenomenon that should occur in many naturalistic settings.

15. SUBJECT TERMS
Systems dynamics modeling; Time course; Recognition-primed decision; RPD; Decision-making processes; Pattern recognition; Conjunction benefits and costs; Decision priming;

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**Public Release**	**26**	

Intuitive decision making (knowing without deliberation) refers to making decisions via steps that are largely unconscious and based on situational pattern recognition. Evans (2003) has suggested that the intuitive system is old in evolutionary terms and that it comprises a set of autonomous subsystems that involve domain-specific knowledge. Many authors have argued that the intuitive system is fast, automatic, relatively effortless, associative, concrete, and related to high-level perception. This system makes use of acquired experience and expertise (Klein et al., 2003). According to Lopes and Oden (1991; see also Chase & Simon, 1973a, 1973b), pattern recognition–based decision making has the advantage of reducing the problem of cognitive inference to one of identification and recognition. This system is good for rendering decisions under stressful conditions involving data overload, high uncertainty, time pressure, high risk, high stakes, and ill-defined goals (Klein, 1997, 1998, 2008; Zsambok & Klein, 1997).

One conceptual model of intuitive decision making is called the recognition-primed decision model by Klein (e.g., 1997, 1998, 2008).

Recognition-Primed Decision Making

Klein (e.g., 1997, 1998, 2008) proposed a conceptual model of intuitive decision making called the *recognition-primed decision (RPD) model*. This model is composed of three components: one for matching, one for diagnosing, and one for simulating a course of action. Figure 1 depicts the matching and diagnosing components; the former is shown by the box labeled "pattern recognition" and the latter by the box labeled "clarify/diagnose (story building)." In this model, an individual with expertise identifies a current problem situation as typical and familiar based upon a composite situation stored in memory and, with subsequent expectations confirmed, initiates an appropriate course of action, which is typically the first one considered. Klein (1997, 1998, 2008) also proposed that an individual may mentally simulate a course of action before actually implementing it (not shown in Figure 1). If the situation is unfamiliar, however, or if subsequent expectations are

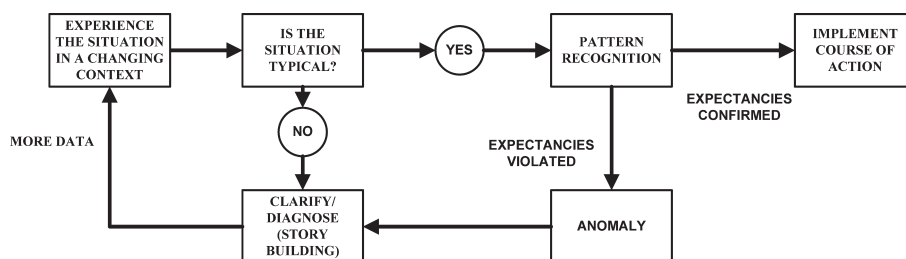*Figure 1. Diagram of the recognition-primed decision model. If an individual experiences a situation as typical and familiar and recognizes the pattern, he or she decides to implement a course of action if expectancies are confirmed. If the situation is atypical and unfamiliar, or if expectancies are violated, then the individual decides to clarify and diagnose the situation, which can involve story building.*

violated, then the individual will choose to diagnose and clarify the situation further, which may include story building.

The basic idea of Klein's (1997, 1998, 2008) RPD model has been empirically supported. For example, Klein, Wolf, Militello, and Zsambok (1995) investigated the moves selected by mediocre and very strong chess players. For both groups of players, the first move selected was typically much stronger than that expected from random sampling. Moreover, Calderwood, Klein, and Crandall (1988; see also Chase & Simon, 1973a, 1973b) found that the error rate of chess experts was low, and remained unchanged, under extreme time pressure (6 s per move) relative to play under regulation conditions (more than 2 min per move). The results of both studies suggested that the chess experts were engaged in pattern matching rather than contrasting multiple options, consistent with assumptions of the RPD model.

In the present paper, we present a formal computational model of the dynamics of Klein's RPD framework employing system dynamics methodology. We focus on the match and diagnose components of Klein's model. These components convey the idea that an initial pattern-matching (situation-matching) process is first undertaken, followed by a subsequent situational assessment that entails a further pattern-matching process that may confirm or violate expectations. If both the initial situational pattern is matched and expectations are subsequently confirmed, then a decision to act is made.

This model implies a framework based on parallel information-processing channels with nested decisional operators (PCNDO). One type of operator would be an XOR gate (XOR refers to an exclusive OR, otherwise known as an *exclusive disjunction operator*), which would exist for a pair of lower-level channels signaling an initial pattern match or nonmatch, and a second XOR gate, which would exist for another pair of lower-level channels signaling expectancies confirmed or violated (i.e., each decision choice or option would be represented by its own channel). The output from the two pairs of channels would be combined with an AND gate, which would lead to a final decision (i.e., an "implement course of action" decision or a "diagnose/clarify" decision, depending upon the particular combination of outputs from the lower-level channels). An analogous type of model has been described by Townsend and Wenger (2004). We will defend this choice of computational architecture later in this paper, in the section on RPD model structure.

This type of system can lead to an interesting phenomenon when decision dynamics are considered, namely *decision priming*. Decision priming can occur when the activation of the two parallel channels is staggered in time. An example of decision priming comes from a set of laboratory phenomena called *conjunction benefits* and *conjunction costs,* which can also be placed in a PCNDO framework.

Conjunction Benefits and Conjunction Costs

In the conjunction benefits and conjunction costs (CBCC) research (Fournier, Bowd, & Herbert, 2000; Fournier, Eriksen, & Bowd, 1998; Fournier, Herbert, & Farris, 2004; Fournier, Patterson, Dyre, Wiediger, & Winters, 2007; Fournier, Scheffers, Coles, Adamson, & Vila, 2000), an individual has to render a judgment

about the presence or absence of a conjunction of two target features in a briefly exposed stimulus. When the two stimulus features differ in their speed of discrimination, correct decisions indicating the presence of the conjunction are faster than correct responses made to the single feature for which discrimination is the slowest. In this case, the feature for which discrimination is the fastest *primes* the decision made about the conjunction. This is called *conjunction benefits*.

Moreover, correct decisions indicating the absence of a conjunction are delayed if the feature for which discrimination is the fastest is present, relative to when neither target feature is present. This also indicates that a single feature can prime decisions made about the conjunction. It is assumed that the target feature for which discrimination is the fastest incorrectly primes a central decision process that the target conjunction is present. Delayed activation resulting from the feature for which discrimination is the slowest must override this primed decision, which takes additional processing time. This is called *conjunction costs*. Overall, the time course of such decision priming is measured in hundreds of milliseconds.

For example, representative data from Fournier et al. (2007) show the following: The reaction time (RT) for rendering a correct "present" decision about the fastest feature by itself was 460 ms, whereas it was 525 ms for the slowest feature. The RT for rendering a correct "present" decision about the conjunction of the two features was 490 ms, which was faster than the RT for the slowest feature, thus showing evidence of conjunction benefits. The RT for rendering a correct "absent" decision about the conjunction was 620 ms when the fastest target feature was present (but the slowest target feature was absent, thus the conjunction was absent), relative to an RT of 490 ms when neither target feature was present, thus showing evidence of conjunction costs.

Note that Fournier and colleagues (Fournier et al., 1998, 2004, 2007; Fournier, Bowd, et al., 2000; Fournier, Scheffers, et al., 2000) have shown that the actual empirical reaction times depend upon stimulus parameters such as stimulus size and contrast, so there is a range of values reported in the literature. The important point is that one stimulus cue must be processed faster than another cue for this kind of decision priming to occur. Many of the assumptions regarding the priming interpretation of this pattern of results have been thoroughly discussed by Fournier and colleagues (see, e.g., Fournier, Bowd, et al., 2000; Fournier et al., 1998, 2007), and therefore these assumptions will not be discussed here.

The purpose of the present study was to take a computational model of the *dynamics* of the CBCC phenomena and generalize that computational structure to Klein's RPD framework. We did so in order to make predictions about intuitive decision making in naturalistic contexts. The prediction that we make from our modeling efforts is that the phenomenon of *decision priming* will occur in naturalistic settings.

Our computational model of the CBCC phenomena was validated by comparing its output with the aforementioned CBCC trends reported by Fournier et al. (2007). (Because the structure of our CBCC model is exactly analogous to our

model of the RPD process, which we will present in detail, in an effort to save space and eliminate redundancy we have decided not to formally present our CBCC model.) Our model RTs were as follows: fastest feature = 438 ms, slowest feature = 538 ms, conjunction present = 513 ms. Thus, simulated RT for the conjunction present response fell between the simulated RT values for the fastest and slowest feature responses, which revealed that the model simulated conjunction benefits. Our model also generated the following RTs: neither feature present (conjunction absent response) = 513 ms, only fastest feature present (also conjunction absent response) = 975 ms. Thus, simulated RT for the conjunction absent response when the fastest feature was present was longer than RT for the same response when neither feature was present, which showed that the model simulated conjunction costs.

We next recalibrated our CBCC model for use as a framework for Klein's RPD model. Changes in system parameters were chosen so that decision making in Klein's model would take 10 to 20 s. This time scale was chosen based on a rough estimate of the timing of decision making by fire ground commanders, as suggested by Klein (personal communication, August 15, 2008). Our computational model of Klein's framework is presented next.

Recently, there have been other reports of models of the RPD process. For example, Warwick, McIlwaine, Hutton, and McDermott (2001) have simulated Klein's RPD model using a resource allocation task and a computational model that implemented a similarity-based recognition routine. Mueller (2009) has developed a model of the RPD process based on a Bayesian decision framework. Although interesting, those efforts did not focus on the dynamics of decision making. In the present study, we simulated the dynamics of several aspects of Klein's RPD model using system dynamics modeling.

System Dynamics Modeling

We wished to implement a computational model of Klein's RPD framework that would focus on the dynamics of the decision-making process. In doing so, the model would not perform any actual pattern recognition, nor would it actually generate expectancies; this is similar to other models of reaction time, such as random walk/diffusion models (see, e.g., Ratcliff, 1978, 2001). Rather, the purpose of the model was to account for the time course of those processes in a way that investigates decision priming. To do so, we used a technique called *system dynamics modeling*. This approach examined the dynamical interactions among model components that produced system behavior.

System dynamics modeling was developed in the 1950s and 1960s by Jay W. Forrester (e.g., 1961, 1968) as an approach for analyzing the dynamics of complex systems that entail feedback loops, such as business systems, urban systems, and ecological systems. The existence of feedback loops complicates system analysis because system output is fed back into the system as input. Feedback loops can produce exponential growth or exponential decay, which may be further modified via higher-order connections, thus creating highly nonlinear behavior. In many

cases, feedback systems possess an equilibrium or set point and thus constitute a control system. In these kinds of systems, behavior varies over time in a complicated manner that cannot be understood by simply looking at the system in a static snapshot. Rather, the dynamics of such systems must be simulated and allowed to evolve over time in order for one to gain a true understanding of system behavior (Sterman, 2000). For example, this approach has been used to model the dynamics of complex systems that have contained hundreds of state variables, such as economic systems (Sterman, 2000).

In system dynamics modeling, computational structures are created that represent systems of differential equations of varying degree. One can create the computational structure of a system by using a small set of elements that are interconnected in complex ways. These elements include a "stock," which is a component representing integration (represented in our diagrams as a rectangle); a "flow," which is a component representing rate of change or a derivative (represented as a thick arrow); a "connector," which is a component representing feedback or other types of connections (shown as a thin arrow); and a "converter," which is a component representing a constant, a variable, an expression, or a conditional logic statement (represented as a circle). It is important to note that these components are not psychological constructs; they are mathematical constructs that serve to model a system of differential equations. The solution to the system of differential equations can be estimated by solving a system of difference equations using a stepwise numerical integration technique.

RPD Model Structure

The system dynamics model of the RPD framework is shown in Figure 2, which is composed of three levels of processing. These three levels flow from the left side of the figure to the right side: (a) integration processes involving different kinds of information, shown going down the left side of the figure; (b) mental events concerning recognition or expectancies, depicted in the middle of the figure; and (c) a central decision process rendering an "implement course of action" decision or a diagnose decision, shown on the right side of the figure.

These three levels of processing correspond to putative human cognitive processes discussed in the CBCC literature (Fournier, Bowd, et al., 2000; Fournier et al., 1998, 2004, 2007; Fournier, Scheffers, et al., 2000). In that literature, it has been assumed that sensory mechanisms exist for the initial capture and integration of information about various sensory dimensions (e.g., hue or shape of a target). Also, it has been assumed that once the initial information becomes integrated, subsequent perceptual processes recognize various aspects of the integrated sensory information. Finally, this literature has posited that the outputs of the recognition processes are combined in the service of making decisions about various combinations of perceptual/situational cues.

Moreover, with respect to our dynamical model of the RPD model, we have assumed that the recognitional process is primarily a perceptual situational-pattern

$$dFSI/dt = [(k1)(FSI)] - [(k1)(FSI)(FSI/C)] \qquad dPR/dt = [(k1)(FSI)(1-(FSI/C))] - [(k1)(PR)]$$
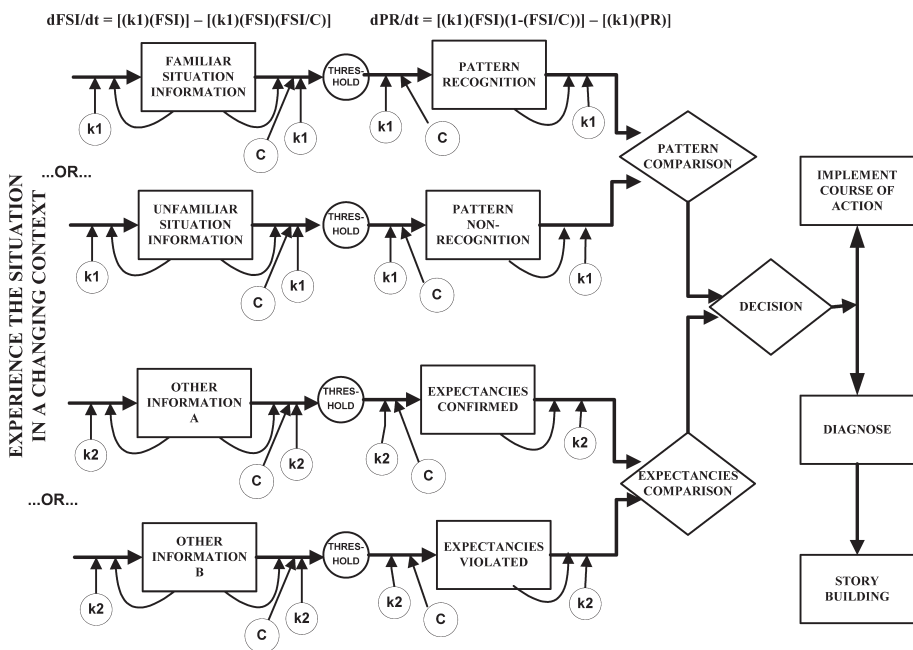
Figure 2. System dynamics model of the recognition-primed decision model. Rectangles down the left side are integrator processes that integrate information about an initial situation or other information. Rectangles down the middle are integrators that represent pattern recognition or expectancies confirmed or violated. Expressions at the top of the diagram are representative of the computation each type of integrator performs. Diamonds represent comparison and logic mechanisms that relate different combinations of inputs to a given decision by the central decision process: implement course of action or diagnose. Pattern comparison and expectancies comparison processes: logical OR decision operators; decision processes shown in diamonds: logical AND decision operators.

recognition process, rather than a high-level cognitive process that entails explicitly elaborated knowledge structures. We based this assumption upon Klein's (1998, p. 32) description of the RPD process, wherein individuals with expertise (i.e., fire ground commanders) made intuitive decisions without initially being aware of the basis for them; in other words, the information underlying the intuitive decisions was tacit or implicit (see also Reber, 1989, p. 232). Also, as discussed earlier, in the RPD model an individual may mentally simulate a course of action before implementing it, which would represent an analytical component of the model (Klein, 2008) and could involve explicitly elaborated knowledge, but this would occur subsequent to the pattern recognition process.

Turning back to Figure 2, the rectangles in the figure are integrators that accumulate various levels of information (evidence), activation, or decision commitment.

These levels have a capacity (C) of 100, meaning that up to 100% of available information could be accumulated, or up to 100% of activation could occur, or up to 100% of commitment could be made for a given decision. Values of $k1$, $k2$, and β were chosen such that decision making took 10 to 20 s and story building took about 1 min. In calibrating our model to these estimates, we took values of $k1$, $k2$, $\beta1$, and $\beta2$ in our CBCC model ($k1 = 2.05$, $k2 = 1.42$, $\beta1 = \pm2.35$, $\beta2 = \pm1.5$) and scaled them so that the output of our RPD model was consistent with those estimates. (Parameter values became $k1 = 1.0$, $k2 = 0.4$, $\beta1 = \beta2 = \pm0.65$.)

Figure 2 shows that the initial situation was represented as a pair of information flows: initial familiar-situation information followed by pattern recognition, or initial unfamiliar-situation information followed by pattern nonrecognition. Subsequent information confirming or violating expectations was also represented as a pair of information flows, with each flow broken into two parts: subsequent other information A followed by expectancies confirmed, or subsequent other information B followed by expectancies violated.

Thus, each lower-level decision (concerning recognition or expectancies) was represented by two flows—one for each decision state or alternative (Smith & Vickers, 1988)—which were combined with an XOR decision operator, and each flow was represented as a discrete two-stage process (Meyer, Yantis, Osman, & Smith, 1985). The processing flows for the lower-level decisions (recognition and expectancies) were combined with an AND operator. Only one flow of each pair—recognition or nonrecognition, and expectancies confirmed or violated—was active at any one point in time. Although this model may at first glance appear overly complicated, the complexity is necessary, given that we are modeling pairs of lower-level decisions that get combined at a higher level, leading to a central (final) decision.

The several assumptions of the model were as follows:

1. Information (evidence) about a particular initial situation, leading to a pattern recognition or nonrecognition response, and subsequent information, leading to expectancies confirmed or violated, accumulated in a time-variant fashion. Such time-variant processes are important for maximizing rewards (i.e., successful action taken) when passage of time may lead to a changing situation that negates the decision-making process (see Ditterich, 2006).
2. Two sets of independent processing streams, with different time courses, operated in parallel to determine decision making. This approach, which involved two XOR decision operators (one for each set of processing streams) nested within a higher-order AND decision operator (which rendered a final decision), was analogous to a version of the PCNDO model of Townsend and Wenger (2004) and was necessary to model decision priming. This approach was different from a classic random walk or diffusion model, in which evidence is accumulated as a single signed total representing differences between the evidence accumulating for different decision alternatives before the decision stage is reached (Busemeyer & Townsend, 1993; Ratcliff, 1978, 2001; Usher & McClelland, 2001).

3. Pattern recognition (both the initial situation and the subsequent information leading to expectancies) was a discrete two-stage process that required a threshold of familiarity to be reached before the next processing stage began. Meyer et al. (1985) suggested that such a framework was appropriate for simple binary decisions when stimuli are mapped to responses in a compatible fashion. The two-stage process was also required for model implementation, in which output from the pattern recognition/nonrecognition stage and from the expectancies confirmed/violated stage was a time-limited response that was integrated by the central decision process.

4. Story building started earlier for an atypical/unfamiliar situation than for a typical/familiar situation with expectancies violated, consistent with the general description of the RPD model (Klein, 1997, 1998, 2008).

5. The time course of decision making depended upon system parameters growth/decay factor k, capacity C, and scaling factor β.

6. In our basic presentation of our model that follows, the model was deterministic and lacked stochasticity, similar to the ballistic accumulator model of Brown and Heathcote (2005). Later in the paper, we will discuss implementing stochastic effects by varying the starting point of the accumulation of information.

7. Our model of dynamics focused solely upon process and ignored knowledge, unlike Klein's RPD framework, which focused mainly upon the role of knowledge and expertise in decision making. These two approaches are complementary: In principle, the dynamics of the system would, in part, be determined by how people use knowledge (implicitly or explicitly). Moreover, whereas process can be dictated, in part, by knowledge, process is also impacted by computational architecture, which was our current focus.

8. For simplicity, we do not implement the cyclic nature of Klein's RPD model, whereby a decision maker may take several passes through the overall process to reach a final decision. This is because implementing the cyclic nature of the model would not directly add anything new about decision priming, which is the main issue explored in our model. To do so would simply require a connection from the story-building process to various pairs of the initial information-integration processes (see Figure 2), which would start model activation all over again.

We now turn to the details of our model.

Initial Integration Processes

The initial integration processes integrate information (evidence) about a given situation. Going down the left side of Figure 2, this information could be consistent with either a familiar situation or an unfamiliar situation and supplemented with subsequent information that either confirmed expectancies ("other information A") or violated expectancies ("other information B"). Integration processes were modeled as capacitated growth processes based on a logistic function (i.e., a time-variant accumulation rate; see Ditterich, 2006), with capacity equal to 100% of information that a given individual could accumulate. The

expression for these initial integration processes, using the familiar-situation information as an example (see Appendix A for all updating equations; see Appendix B for the program code), was

$$\text{net growth rate of information} = \frac{dFSI}{dt} = (k \cdot FSI) - \left(k \cdot FSI \cdot \frac{FSI}{C} \right), \tag{1}$$

in which FSI = familiar situation information, t = time, k = growth or decay fraction (in which $k = k1, k2$), and C = capacity. In system dynamics, the logistic function is modeled as a set of coupled positive and negative feedback loops, with $kFSI$ defining the positive feedback loop (growth) and $-kFSI(FSI/C)$ defining the negative feedback loop (decay). Here, $k1 > k2$; thus situational information accumulated at a faster rate than did other information.

The model represented a given decision-making scenario by activating a given combination of initial integration processes with a starting value of 10—for example, $FSI(0) = 10$. To deactivate, initial value was 0. This initial value was arbitrary, and the model could be calibrated to accommodate any other small initial value. Thus, to simulate the scenario of a familiar situation with expectancies confirmed, for example, the information integration processes labeled "familiar situation information" and "other information A" were started with a value of 10, whereas the information integration processes labeled "unfamiliar situation information" and "other information B" were started with a value of 0.

A threshold mechanism with a criterion value of 50 units followed each information integration mechanism. A threshold setting of 50 units meant that more than half of the perceptual information must have been accumulated before subsequent processing could respond, which is consistent with the traditional definition of threshold (Blake & Sekuler, 2005). The existence of this threshold created a time delay, and therefore a discrete two-stage processing flow, consistent with suggestions by Meyer et al. (1985). For instance, for familiar situation information,

$$\text{IF FSI} > 50, \text{THEN FSI. ELSE } 0. \tag{2}$$

Recognition/Expectancy Mechanisms

The mechanisms for pattern recognition and expectation (middle portion of Figure 2) integrated the information from the initial integration processes to generate a time-limited response: an initial recognition or nonrecognition response, and an expectancies confirmed or expectancies violated response (the latter of which was also conceptually equivalent to a recognition response). The response of these mechanisms was a rounded pulse profile that decayed to zero when the corresponding prior initial integration process (Equation 1) reached full capacity. Here, the concept was that as information about a familiar situation became integrated, the pattern recognition mechanism began to generate an initial recognition response that ended when all the information about that situation had been accumulated. (A time-limited response was also needed so that the amount of decision

commitment by the central mechanism would level off once the time-limited response decayed to zero, which allowed the recognition response and the expectancies response each to contribute to one half of the final decision.)

Accordingly, the net growth rate of these recognition/expectancy mechanisms, using the pattern recognition mechanism as example, was

$$\frac{dPR}{dt} = \left[\left(k \cdot FSI \right) \cdot \left(1 - \frac{FSI}{C} \right) \right] - \left(k \cdot PR \right), \tag{3}$$

in which *PR* is the level of activation of the pattern recognition response and *FSI, k, t,* and *C* are as defined previously. Here, the input to the mechanism is a *k*-weighted *FSI* variable, and $-kPR$ is a negative feedback decay loop: As *FSI* reached capacity, $1 - FSI/C$ went to zero, the input ceased, and then the accumulation decayed.

Output from these recognition and expectancy mechanisms projected to processes called "pattern comparison" and "expectancies comparison," each of which compared either two types of situational patterns or two types of expectancies to determine whether the information being integrated by the pattern and expectancy mechanisms was consistent with an "implement course of action" decision (if not, then a sign change was implemented, which affected the final decision):

IF (pattern recognition > pattern nonrecognition) THEN
(pattern recognition * β) ELSE (pattern nonrecognition * −β), (4)

in which β was a scaling factor that kept information emanating from the pattern comparison and the expectancies comparison mechanisms balanced (so that each type of signal contributed to one half of the total response of the central decision process). The output from these two comparison mechanisms projected to the central decision process for rendering a final decision.

Central Decision Process

The central decision process rendered a final decision to either implement a course of action or to diagnose the situation further (leading to a story-building algorithm). The central decision process integrated information from the two comparison mechanisms and determined whether both a familiar situation was perceived and other information confirmed expectations. The central decision process was composed of two interconnected *decision reservoirs*, and was activated by a logic statement (called "Decision" in the diamond in Figure 2) that compared the streams of information coming from the pattern comparison process and expectancies comparison process to determine which combination was present:

IF [(pattern comparison > 0) AND (expectancies comparison > 0)] OR
[(expectancies comparison > 0) AND (pattern comparison > 0)] THEN
[MAX (pattern comparison, expectancies comparison) * −1] + MIN (5)
(pattern comparison, expectancies comparison) ELSE
(pattern comparison + expectancies comparison).

This logic combines signals from the two comparison mechanisms in an additive fashion. If output from one comparison mechanism is positive and output from the other comparison mechanism is negative, then the output from the positive mechanism (i.e., the MAX function) is multiplied by −1 and added to the output of the negative mechanism (the MIN function) to yield a negative flow affecting the central decision process (leading to a "diagnose" decision). If the output from both comparison mechanisms is negative, then processing goes to the ELSE statement, which simply adds two negative flow rates to yield a negative flow affecting the central decision process (again, a "diagnose" decision). If output from the two comparison mechanisms is positive, then processing goes to the ELSE statement, which adds two positive flows to yield a positive flow rate affecting the central decision process (an "implement course of action" decision).

Each decision reservoir symbolized the amount of decision commitment for each decision: "implement course of action" or "diagnose the situation." The simulation began with decision ambiguity (50 in each of the two reservoirs). Over time, the amount of decision commitment flowed from one reservoir into the other, depending on incoming evidence from pattern and expectancies comparison processes. The rate of flow into or out of one or the other decision reservoir was determined by the sum of the activation levels of the comparison mechanisms. For the "implement course of action" reservoir,

$$ICA = \int CDGR dt + ICA(0), \tag{6}$$

in which ICA = reservoir containing the level of commitment to the "implement course of action" decision, $CDGR$ was the central decision growth rate = (pattern comparison + expectancies comparison), and $ICA(0)$ was the initial value of ICA, in which $ICA(0)$ = 50. Equation 6 indicates that activations of the pattern comparison mechanism and expectancies comparison mechanism were added and the sum projected to the central decision process as a rate, which ended up being integrated by the central decision process to become an increasing level of decision commitment. An analogous definition would apply to the "diagnose" reservoir.

For each simulated decision, one reservoir accumulated a total of 100 percentage points, representing complete commitment to the corresponding option, whereas the other reservoir went to 0, representing a complete abandonment of the opposing option.

Modeling Results and Analysis

Deterministic Model

The model we have described was implemented using the Stella software package, version 9.2 (ISEE Systems, Inc., Waltham, MA). The Euler method of numerical integration (Sterman, 2000) was used with $dt = 0.1$. For the pattern comparison process, $k1 = 1.0$ and $\beta = \pm 0.65$; for the expectancies comparison process, $k2 = 0.4$ and $\beta = \pm 0.65$.
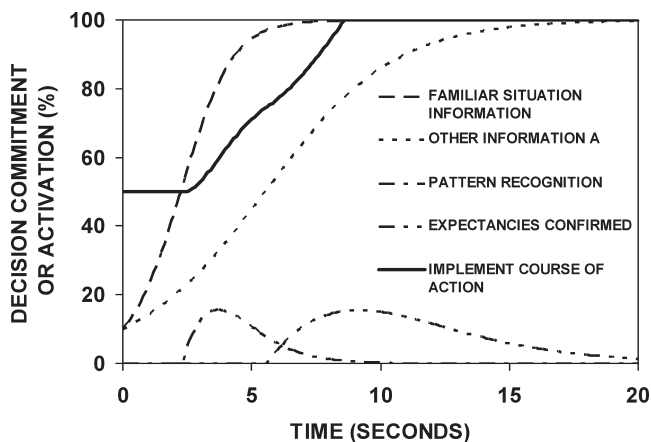
Figure 3. "Implement course of action" decision with a typical and familiar situation and expectancies confirmed. Time course of the percentage decision commitment or activation is shown for various model components. The dashed line shows the integration of information about an initial typical/familiar situation, which leads to a pattern recognition response as indicated by the dash-dot-dash line. The dotted line shows the integration of other information A, which leads to an expectancies-confirmed response as indicated by the dash-dot-dot line. The thick solid line shows the time course of the final decision to implement course of action (which took about 8 s).

We ran simulations of model responding for various combinations of pattern and expectancy conditions. Figure 3 shows the results of a simulation of the "implement course of action" decision, which involved initial recognition of a familiar situation and having expectancies confirmed. The dashed and the dash-dot-dash curves, respectively, show the integration of the familiar situation information and the response of the pattern recognition mechanism. The dot and the dash-dot-dot curves, respectively, show the integration of other information A and the response of the expectancies-confirmed mechanism. It can be seen that the recognition of a familiar situation occurred first, followed by the confirmation of expectancies, as the logic of this scenario dictates. The final decision to implement a course of action (100% decision commitment) took about 8 s.

Figure 4 shows the results of a simulation of the "diagnose" decision, which involved nonrecognition of an atypical or unfamiliar situation and the presence of other information B, which produced an expectancies-violated response. The dashed and the dash-dot-dash curves, respectively, show the integration of the unfamiliar situation information and the response of the nonrecognition process. The dot and the dash-dot-dot curves, respectively, show the integration of other information B and the response of the process registering that expectancies were violated. Recognition that the situation was unfamiliar occurred first, followed by a violation of expectancies. The final decision to diagnose the situation further (100% decision commitment) took about 8 s.
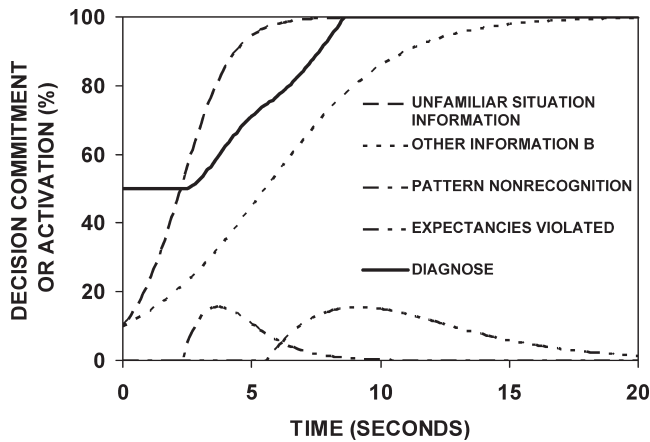
Figure 4. "Diagnose situation further" decision with an unfamiliar situation and expectancies violated. Time course of the percentage decision commitment or activation is shown for various model components. The dashed line shows the integration of information about an initial unfamiliar situation, which leads to a pattern nonrecognition response as indicated by the dash-dot-dash line. The dotted line shows the integration of other information B, which leads to an expectancies-violated response, as indicated by the dash-dot-dot line. The thick solid line shows the time course of the final decision to diagnose the situation.

Figure 5 shows the results of a simulation of the "diagnose" decision, which involved initial recognition of a typical and familiar situation, but the presence of other information B led to an expectancies-violated response. Here, the initial information that the situation was familiar primed the central decision process to begin to decide to "implement a course of action" (i.e., curve labeled "diagnose" begins to dip down between 2 and 6 s in the simulation), but subsequent information B produced an expectancies-violated response, and the central decision process reversed itself and eventually produced a decision to "diagnose." The final decision to diagnose the situation (100% decision commitment) took about 16 s.

This delay in rendering a "diagnose" decision (16 s in Figure 5 vs. 8 s in Figure 4) because of the presence of conflicting information is thought to be the result of decision priming. Decision priming occurred in the present context when a given situation was recognized and the decision to implement a course of action was primed but subsequent information violated expectations, which eventually led to a decision for diagnosis. The decision to diagnose was delayed relative to when the initial situation was unfamiliar and a decision to implement a course of action had not yet been primed. This decision priming, in which an initial situation that appeared typical and familiar and thus was initially recognized but subsequent expectancies were violated, was analogous to the phenomenon of conjunction costs discussed earlier (Fournier et al., 1998, 2004, 2007; Fournier, Bowd, et al., 2000; Fournier, Scheffers, et al., 2000).
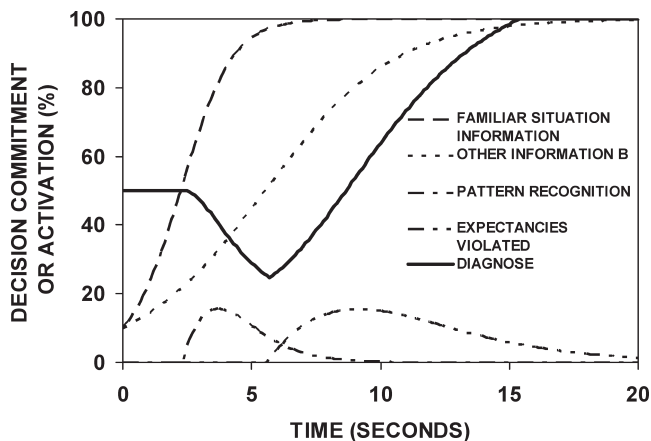
Figure 5. "Diagnose the situation further" decision with a typical and familiar situation but expectancies violated. Time course of the percentage decision commitment or activation is shown for various model components. The dashed line shows the integration of information about an initial typical/familiar situation, which leads to a pattern recognition response, as indicated by the dash-dot-dash line. The dotted line shows the integration of other information B, which leads to an expectancies-violated response, as indicated by the dash-dot-dot line. The thick solid line shows the time course of the final decision to diagnose the situation. The initial dip in the diagnose curve between 2 and 6 s is attributable to decision priming: Information about a familiar situation primed the central decision process to begin to decide to implement a course of action (this curve dips down away from the commitment to diagnose), but subsequent other information B indicated the need for a decision to diagnose, which was finally rendered after an 8-s delay (compare with Figure 4).

Figure 6 shows the same simulation results that were depicted in Figure 5 across a longer time scale. (The curve for "implementing a course of action" decision has also been added.) This time scale permits one to see the time course of story building, which was initiated by the decision to diagnose and took about 60 s from the beginning of the simulation to complete. This process of story building was modeled as a logistic function (analogous to Equation 1, with $k = 0.15$), with 100% indicating the total amount that a story could be mentally built in a given situation.

The model took 8 s to decide to implement a course of action and between 8 and 16 s to decide to diagnose a situation further (depending upon the presence or absence of conflicting information). The model took an additional 60 s to perform a story-building operation following the decision for diagnosis (see Figure 7).

As discussed by Klein (1997, 1998, 2008), an individual may mentally simulate a course of action before actually implementing it, which may take about the same amount of time as the process of story building (i.e., the act of mental simulation is a form of story building). This act of mental simulation would occur
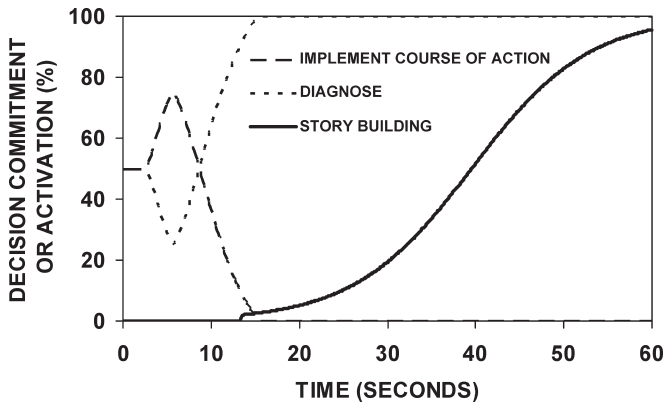
Figure 6. Same as Figure 5 ("diagnose the situation further" decision with a typical and familiar situation but expectancies violated) but with the time course of decision commitment or activation shown with an extended time scale. The dotted line indicates the decision to diagnose the situation; the dashed line shows the "implement course of action" decision, which has been added to this figure. The thick solid line represents the time course of story building.

between the pattern recognition process and the decision to implement a course of action in Figure 7, assuming that expectancies are confirmed. In our simulation of the RPD model, mental simulation would add an additional 60 s to the "implement course of action" decision (figure not shown) and appear analogous to the curve depicting the story-building process shown in Figure 6.

Stochastic Effects

In exploring the role of stochastic effects on model behavior, we needed to choose from among a large set of possible implementations. To narrow our options,
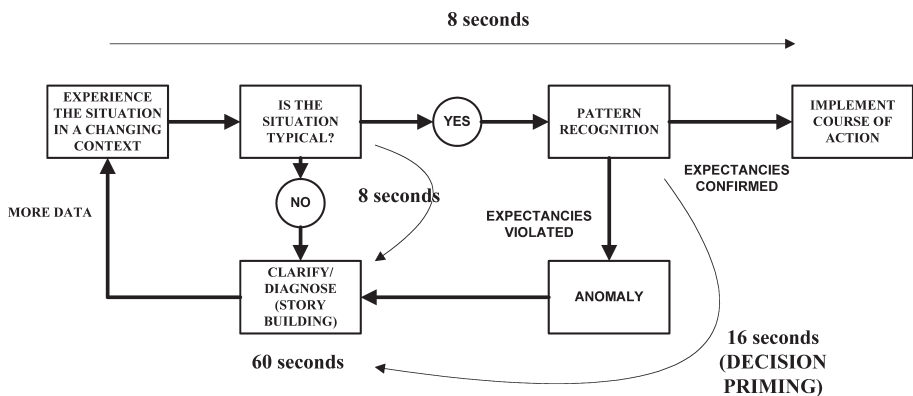

Figure 7. Diagram of the recognition-primed decision model (Klein, 1997, 1998, 2008), shown with the simulated latencies for decision making and story building.

we chose to examine the effect of variation in the starting point of information accumulation, which corresponded to the existence of a decision bias and has been a common manipulation in many random walk/diffusion models (e.g., Ratcliff, 1978, 2001). Moreover, because we were primarily interested in decision priming in this study, we elected to study the scenario involving the recognition of a familiar situation but with violated expectancies. Recall that this scenario produced an additional delay in decision making of 8 s relative to when an initial situation was unfamiliar and not recognized (see Figure 5). We used the simulated outcome in Figure 5 as the benchmark with which the effects of variation in starting point were compared.

We simulated the decision-priming scenario with different values of $FSI(0)$—that is, when $FSI(0) = 1, 2, 5, 20,$ or 50; recall that in our deterministic model, $FSI(0) = 10$. As before, we kept $OIB(0) = 10$ (in which OIB = other information B). The results revealed that the corresponding simulated reaction times to make a "diagnose the situation further" decision were, respectively, 9.7, 11.0, 13.4, 17.5, and 21.7 s; recall that when $FSI(0) = 10$, the simulated RT was 15.5 s.

Thus, we found that as the starting point of information accumulation for the familiar situation was decreased from its initial value of 10, decision priming was lessened. This would correspond to the existence of a decision bias against seeing the initial situation as being typical and familiar and its pattern being recognized. As the starting point of information accumulation for the familiar situation was increased, decision priming increased. This would correspond to the existence of a decision bias toward seeing the initial situation as being typical and familiar and its pattern being recognized.

Discussion

Klein (1997, 1998, 2008) has proposed a conceptual framework of intuitive decision making called the recognition-primed decision (RPD) model. In order to model the dynamics of Klein's framework, we created a parallel-channels, nested decision operator model (PCNDO; see Townsend & Wenger, 2004), which was based on a system dynamics model of the conjunction benefits and conjunction costs phenomena (e.g., Fournier, Bowd, et al., 2000; Fournier et al., 1998, 2007). In our model, there were two types of decisional operators: an XOR gate that existed for each of two pairs of lower-level channels, followed by an AND gate that combined the outputs of the two pairs of channels. With staggered timing between the two pairs of channels, a phenomenon called decision priming could be simulated.

In more concrete terms, simulated priming occurred when a familiar initial situation occurred with subsequent violated expectancies: The familiar situation primed activation of the central decision process to begin to decide to implement a course of action, so that when expectancies were violated, the final decision to "diagnose" took longer than when an initial situation was unfamiliar. The cost of decision priming was a decision delay of 8 s. Generally, our simulation of the RPD

model suggests that the time it takes to make pattern-based decisions may be affected by whether incoming information is compatible or conflicting. Conflicting information can lead to decision priming, whereby a tendency to decide one way is counteracted by subsequent information, a process that delays overall decision making. Therefore, although intuitive decision making based on pattern recognition reduces the problem of cognitive inference to one of identification and recognition (Lopes & Oden, 1991) and thus is highly efficient, it may be vulnerable to conflicting cues and information.

An analogous pattern of results would occur with changes in temporal scale, and a recalibration of model parameters for representing different decision scenarios, so long as the relative timing is lagged between one set of environmental cues and patterns and a conflicting set of cues and patterns. Accordingly, the model presented in this paper can be expanded to encompass a wide range of situations that entail intuitive decision making involving potentially conflicting information. This model represents a class of race models in which the differential timing of multiple events can create decision priming (Fournier et al., 1998, 2004, 2007; Fournier, Bowd, et al., 2000; Fournier, Scheffers, et al., 2007).

One way the validity of this model can be tested and falsified would be to empirically determine whether decision priming actually occurs in the contexts within which Klein's RPD model would be operative. On this point, it is interesting to note that Mitchell and Flin (2007) recently reported that they failed to find evidence for decision priming when police-authorized firearms officers were responding to potential threats in a firearms training simulator. Klein's RPD model would be applicable to this type of situation. In an attempt to induce decision priming, these authors had the officers hear a threat or neutral briefing information prior to experiencing shoot or no-shoot scenarios. The results showed that the type of briefing had no effect on the officers' decision to shoot.

One reason for the failure to observe decision priming in the Mitchell and Flin (2007) study may be that priming, in general, does not occur in naturalistic settings and therefore the CBCC model was not an appropriate foundation for our system dynamics model of the RPD model. However, a recent study by Winterbottom et al. (2009) found that decision priming occurred in a U.S. Air Force simulated air-to-ground attack decision scenario, which entailed vehicles (i.e., tanks) positioned on a ground plane (desert scene) seen in perspective view. Thus, decision priming did occur in a simulated naturalistic setting.

A second reason for the failure to observe decision priming in the Mitchell and Flin (2007) study may be that the generalization of the CBCC computational model to the RPD model was flawed. However, we think that this is unlikely, given that the same computational structures were used and we varied only four model parameters in order to recalibrate the model to the new time scale.

A third reason for the failure to observe decision priming in the Mitchell and Flin (2007) study may be that the decision-making process would be inherently intuitive and therefore be driven by situational pattern recognition (i.e., the officers had only seconds or less to decide whether to shoot back at the virtual

suspect, based on what they perceived in the scene), whereas the briefing information was given verbally. Because symbolic and verbal material are related to the analytical reasoning process (e.g., Evans, 2008; Hammond, 2007; Hogarth, 2001; Kahneman & Frederick, 2002; Sloman, 1996; see especially Hammond, Hamm, Grassia, & Pearson, 1997), the briefing information may have had less of an impact on intuitive decision making than if these authors had used a perceptual priming stimulus. In other words, it may be more difficult for analytical processing to prime intuitive processing than for intuitive processing to prime intuitive processing, a conjecture supported by the conjunction benefits and conjunction costs literature. Our system dynamics model of Klein's RPD framework involves perceptual/situational (intuitive) priming stimuli.

In order to validate our model in the absence of quantitative predictions in the intuitive decision-making literature, we could expand our model to incorporate analytical decision making and the inability of the latter to prime intuitive decision making, as shown by Mitchell and Flin (2007). We intend to do so over the next couple of years; thus, in what follows we provide only a brief sketch of this expanded model. Based on the framework by Hogarth (2005), we would create two basic streams of processing: an intuitive pattern recognition stream (which would include all of the PCNDO structure) and an analytical stream. The analytical stream would include working memory. Both the intuitive stream and the analytical stream would have bidirectional connections to long-term memory, and both would feed a central decision process. To account for the Mitchell and Flin result, several architectures are possible: (a) no links between the two streams; (b) links between the two streams, the activation of which requires precise timing; and (c) links between the two streams which are modulated by emotional arousal.

If validated, and with further elaboration, our model might potentially be useful in the development of decision support tools and training aids for robust decision making. *Robust decision making* refers to the act of making efficient (but not necessarily optimal) decisions under conditions of high uncertainty (Ullman, 2006). In practice, robust decision making may also include the need for making rapid decisions under stress. The term *robustness* is important, for it means that the decision-making process should be successful under a wide range of conditions. In the field of systems science, robustness means that decision rules are operationally meaningful even when inputs to the system take on extreme values (Sterman, 2000, pp. 519).

In recent times, attempts to make decision making robust have typically involved statistical approaches, which deal with high levels of uncertainty in information, utilities, or probabilities (e.g., Krokhmal, Murphey, Pardalos, Uryasev, & Zrazhevsky; 2003; Regan et al., 2005). However, another approach to robust decision making, largely ignored by mainstream decision science, would be based on intuitive decision making. This is because intuition and its attendant pattern recognition is good for rendering decisions under stressful conditions involving data overload, high uncertainty, time pressure, high risk, high stakes, and ill-defined goals (Klein, 1997, 1998, 2008; Zsambok & Klein, 1997). Thus, intuitive reasoning could be a foundation for promoting robust decision making.

We could also increase the complexity of our model to deal with multiple priming stimuli, which may help predict conditions under which priming would be enhanced versus conditions under which it would be eliminated. This information, in turn, could help in the design of immersive decision environments by creating perceptual cues that are selectively presented and timed in order to prime decision making toward a certain response when an individual would be overwhelmed by information overload. The present effort at modeling the recognition-primed decision model of Klein (1997, 1998, 2008) represents a step in this direction.

Appendix A

Here are the updating equations used in our RPD model.

Initial Integration Processes

For the net growth rate of familiar situation information,

$$dFSI/dt = (k1 \cdot FSI) - (k1 \cdot FSI \cdot FSI/C),$$

in which FSI = familiar situation information, t = time, $k1$ = growth or decay fraction, and C = capacity.

For the net growth rate of unfamiliar situation information,

$$dUSI/dt = (k1 \cdot USI) - (k1 \cdot USI \cdot USI/C),$$

in which USI = unfamiliar situation information and t, $k1$, and C are as defined previously.

For the net growth rate of other information A,

$$dOIA/dt = (k2 \cdot OIA) - (k2 \cdot OIA \cdot OIA/C),$$

in which OIA = other information A, $k2$ = growth or decay fraction, and t and C are as defined previously.

For the net growth rate of other information B,

$$dOIB/dt = (k2 \cdot OIB) - (k2 \cdot OIB \cdot OIB/C),$$

in which OIB = other information B and t, $k2$, and C are as defined previously.

Recognition/Expectancy Mechanisms

For the net growth rate of the pattern recognition mechanism,

$$dPR/dt = [(k1 \cdot FSI) \cdot (1 - FSI/C)] - (k1 \cdot PR),$$

in which PR is the level of activation of the pattern recognition response and FSI, $k1$, t, and C are as defined previously.

For the net growth rate of the pattern nonrecognition mechanism,

$$dPNR/dt = [(k1 \cdot USI) \cdot (1 - USI/C)] - (k1 \cdot PNR),$$

in which PNR is the level of activation of the pattern nonrecognition response and USI, $k1$, t, and C are as defined previously.

For the net growth rate of the expectancies confirmed mechanism,

$$dEC/dt = [(k2 \cdot OIA) \cdot (1 - OIA/C)] - (k2 \cdot EC),$$

in which *EC* is the level of activation of the expectancies confirmed response and *OIA, k2, t,* and *C* are as defined previously.

For the net growth rate of the expectancies violated mechanism,

$$dEV/dt = [(k2 \cdot OIB) \cdot (1 - OIB/C)] - (k1 \cdot EV),$$

in which *EV* is the level of activation of the expectancies violated response, and *OIB, k2, t,* and *C* are as defined previously.

Appendix B

Here is the program code for our RPD model.

```
Diagnose(t) = Diagnose(t − dt) + (− Central_Decision_Growth_Rate) * dt
INIT Diagnose = 50
OUTFLOWS:
Central_Decision_Growth_Rate = Decision_Logic
Expectancies_Confirmed(t) = Expectancies_Confirmed(t − dt) + (EC_Growth_
Rate − EC_Decay_Rate) * dt
INIT Expectancies_Confirmed = 0
INFLOWS:
EC_Growth_Rate = OIA_Threshold * EC_Growth_Fraction * (1−(OIA_Threshold/
EC_Capacity))
OUTFLOWS:
EC_Decay_Rate = Expectancies_Confirmed * EC_Decay_Fraction
Expectancies_Violated(t) = Expectancies_Violated(t − dt) + (EV_Growth_Rate −
EV_Decay_Rate) * dt
INIT Expectancies_Violated = 0
INFLOWS:
EV_Growth_Rate = OIB_Threshold * EV_Growth_Fraction * (1−(OIB_Threshold/
EV_Capacity))
OUTFLOWS:
EV_Decay_Rate = Expectancies_Violated * EV_Decay_Fraction
Familiar_Situation_Information(t) = Familiar_Situation_Information(t − dt) +
(FSI_Growth_Rate − FSI_Decay_Rate) * dt
INIT Familiar_Situation_Information = 10
INFLOWS:
FSI_Growth_Rate = Familiar_Situation_Information * FSI_Growth_Fraction
OUTFLOWS:
FSI_Decay_Rate = Familiar_Situation_Information * FSI_Decay_Fraction *
(Familiar_Situation_Information/FSI_Capacity)
Implement_Course_of_Action(t) = Implement_Course_of_Action(t − dt) +
(Central_Decision_Growth_Rate) * dt
```

INIT Implement_Course_of_Action = 50
INFLOWS:
Central_Decision_Growth_Rate = Decision_Logic
Other_Information_A(t) = Other_Information_A(t − dt) + (OIA_Growth_Rate −
OIA_Decay_Rate) * dt
INIT Other_Information_A = 0
INFLOWS:
OIA_Growth_Rate = Other_Information_A * OIA_Growth_Fraction
OUTFLOWS:
OIA_Decay_Rate = Other_Information_A * OIA_Decay_Fraction * (Other_
Information_A/OIA_Capacity)
Other_Information_B(t) = Other_Information_B(t − dt) + (OIB_Growth_Rate −
OIB_Decay_Rate) * dt
INIT Other_Information_B = 10
INFLOWS:
OIB_Growth_Rate = Other_Information_B * OIB_Growth_Fraction
OUTFLOWS:
OIB_Decay_Rate = Other_Information_B * OIB_Decay_Fraction * (Other_
Information_B/OIB_Capacity)
Pattern_NonRecognition(t) = Pattern_NonRecognition(t − dt) + (PNR_Growth_
Rate − PNR_Decay_Rate) * dt
INIT Pattern_NonRecognition = 0
INFLOWS:
PNR_Growth_Rate = USI_Threshold * PNR_Growth_Fraction * (1−(USI_
Threshold/PNR_Capacity))
OUTFLOWS:
PNR_Decay_Rate = Pattern_NonRecognition * PNR_Decay_Fraction
Pattern_Recognition(t) = Pattern_Recognition(t − dt) + (PR_Growth_Rate −
PR_Decay_Rate) * dt
INIT Pattern_Recognition = 0
INFLOWS:
PR_Growth_Rate = FSI_Threshold * PR_Growth_Fraction * (1−(FSI_Threshold/
PR_Capacity))
OUTFLOWS:
PR_Decay_Rate = Pattern_Recognition * PR_Decay_Fraction
Story_Building(t) = Story_Building(t − dt) + (SB_Growth_Rate + SB_Initialization
− SB_Decay_Rate) * dt
INIT Story_Building = 0
INFLOWS:
SB_Growth_Rate = Story_Building * SB_Growth_Fraction
SB_Initialization = IF (Diagnose > 90) AND (Diagnose < 91) THEN 10 ELSE 0
OUTFLOWS:

SB_Decay_Rate = Story_Building * SB_Decay_Fraction * (Story_Building/SB_Capacity)

Unfamiliar_Situation_Information(t) = Unfamiliar_Situation_Information(t − dt) + (USI_Growth_Rate − USI_Decay_Rate) * dt

INIT Unfamiliar_Situation_Information = 0

INFLOWS:

USI_Growth_Rate = Unfamiliar_Situation_Information * USI_Growth_Fraction

OUTFLOWS:

USI_Decay_Rate = Unfamiliar_Situation_Information * USI_Decay_Fraction * (Unfamiliar_Situation_Information/USI_Capacity)

Decision_Logic = IF(Expectancies_Comparison > 0) AND (Pattern_Comparison > 0) OR (Pattern_Comparison > 0) AND (Expectancies_Comparison > 0) THEN (MAX(Expectancies_Comparison, Pattern_Comparison) * −1) + MIN (Expectancies_Comparison, Pattern_Comparison) ELSE (Expectancies_Comparison + Pattern_Comparison)

EC_Capacity = 100

EC_Decay_Fraction = 0.4

EC_Growth_Fraction = 0.4

EV_Capacity = 100

EV_Decay_Fraction = 0.4

EV_Growth_Fraction = 0.4

Expectancies_Comparison = IF(Expectancies_Confirmed > Expectancies_Violated) THEN (Expectancies_Confirmed * 0.65) ELSE (Expectancies_Violated * −0.65)

FSI_Capacity = 100

FSI_Decay_Fraction = 1

FSI_Growth_Fraction = 1

FSI_Threshold = IF(Familiar_Situation_Information > 50) THEN Familiar_Situation_Information ELSE 0

OIA_Capacity = 100

OIA_Decay_Fraction = 0.4

OIA_Growth_Fraction = 0.4

OIA_Threshold = IF(Other_Information_A > 50) THEN Other_Information_A ELSE 0

OIB_Capacity = 100

OIB_Decay_Fraction = 0.4

OIB_Growth_Fraction = 0.4

OIB_Threshold = IF(Other_Information_B > 50) THEN Other_Information_B ELSE 0

Pattern_Comparison = IF(Pattern_Recognition > Pattern_NonRecognition) THEN (Pattern_Recognition * 0.65) ELSE (Pattern_NonRecognition * −0.65)

PNR_Capacity = 100

PNR_Decay_Fraction = 1

PNR_Growth_Fraction = 1

PR_Capacity = 100

PR_Decay_Fraction = 1
PR_Growth_Fraction = 1
SB_Capacity = 100
SB_Decay_Fraction = 0.15
SB_Growth_Fraction = 0.15
USI_Capacity = 100
USI_Decay_Fraction = 1
USI_Growth_Fraction = 1
USI_Threshold = IF(Unfamiliar_Situation_Information > 50) THEN Unfamiliar_ Situation_Information ELSE 0

Acknowledgments

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